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Various and multilevel of wavelet transform for classification misalignment on induction motor with quadratic discriminant analysis

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ABSTRACT

Induction motors have become a major part of the industry because of strong construction, cheap in purchasing and maintenance, high efficiency, and easy to operate. Preventive maintenance must always be carried out on all industrial equipment, including induction motors to last long and prevent further damage. Based on research in the industry, around 42%-50% or almost 50% is bearing damage. One reason is the occurrence of misalignment during the installation of the load on the induction motor. This study tries to identify the condition of the motor and classify the level of misalignment damage that occurs. In the process, the mother wavelet like as Daubechis, Symlet and Coiflet discrete wavelet transform (DWT) are selected as tools in processing motor vibration data. The level of DWT applied is 1st to 3rd level. Then, the three types of signal extraction, namely sum, range, and energy, which are obtained from a high-frequency signal of DWT, are used as input to Quadratic and Linear Discriminant Analysis. Then, discriminant analysis analyzes and classifies them into normal operation and two misalignments conditions. The simulation shows that 1st level of Daubechis DWT combined with quadratic discriminant analysis generates the best classification. It results 0% error of classification with Db3, Db4 and Db5, 4.17% error with Db1 and 8.33% error with Db2.

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1. INTRODUCTION

Since it was first discovered, induction motors have become a major part of the industry. That is because the induction motor has strong construction, is cheap in purchasing and maintenance, high efficiency at rated speed and torque, and easy to operate [1-3]. The motor is operated in a humid, dirty, hot environment, etc., which can effect breakdown to parts of the motor. Preventive treatment is needed to prevent defect, extend motor life, and find early breakdown to the induction motor. Defect of insulation and windings is the most common type of breakdon. Bearing defects are 42%-50% of all motor breakdown [4-8]. Bearing motors are valuable between 3%-10% of the actual motor cost. However, the fee due to downtime that occur, so that the production target is not achieved makes bearing failure become very expensive. In general this is caused by production errors, lack of lubrication, and installation errors. Motor misalignment is one of the installation errors.

Misalignment is a condition in which deviations occur at the midpoint between two searching axes. If the clutch experiences a misalignment, the clutch will be damaged quickly and cause a lot of vibration [9]. The previous method used predictive treatment in detecting motor defect. That is, a manual inspection is carried out by the operator to inspect the motor. Thus, the motor needs to be turned off so that operator safety is guaranteed. This of course requires a lot of time and cost. In addition, the quality of checks varies depending on the operator carrying out the maintenance. Therefore, to overcome the problems above a method was developed to detect motor damage from the vibration signal characteristics.

One method for detecting fault on induction motor is using the MCSA method. The MCSA monitors interference by analyzing the stator circulation. MCSA uses the FFT method in analyzing motor current signals [10, 11]. In addition, the use of motor vibration can also be used to detect fault of induction motor. This is because motor fault will produce several effects, one of which is the vibration of the induction motor. A study has been conducted to compare the MCSA method and vibration method [12]. This study shows that the MCSA's ability and vibration method to detect misalignment produce similar curve patterns. However, this study has not applied a detection algorithm.

This research classify process of misalignment and level of misalignment in induction using mother wavelet, including Daubechis, Coiflet and Symlet discrete wavelet transform (DWT) and Discriminant Analysis. Induction motors that are operated and engineered so that under three condition of operation. And then, Daubechis, Coiflet and Symlet DWT from level of 1^{st} to 3^{rd} is applied to generate vibration signal of motor in detil signal or high frequency signal. Then, Feature extraction, including range, sum, and energy, generated from detil signals is collected. Quadratic and linear discriminant analysis (QDA and LDA) verifies and classifies motor data into three conditions of motor.

2. RESEARCH METHOD

General description of the method to be worked is shown in Figure 1. The vibration signal from the induction motor will be taken by piezoelectric sensor. And then, it will be stored on the SD Card by the microcontroller. Furthermore, vibration data consisting of motor vibration data in normal operation, misalignment of 1 mm and misalignment of 1.5 mm will be processed using Daubechis, Symlet and Coiflet DWT in level of 1^{st} to 3^{rd}. DWT results taken for further processing are high frequency signals. The high frequency signal is processed to take the range, sum and energy variables to be applied as input for QDA and LDA. The output of QDA and LDA is motor condition under normal operation, misalignment of 1 mm and misalignment of 1.5 mm.

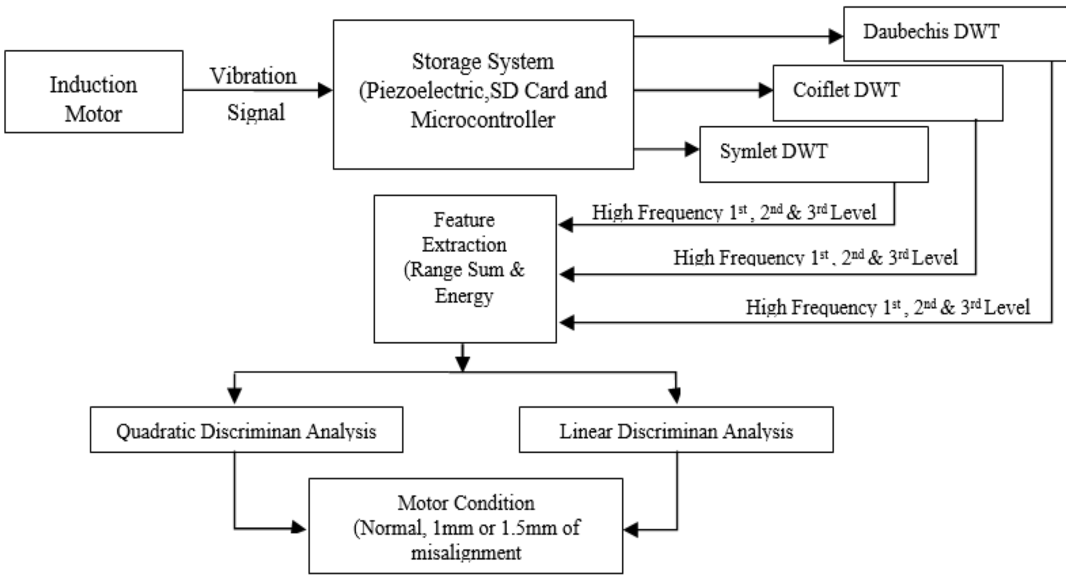
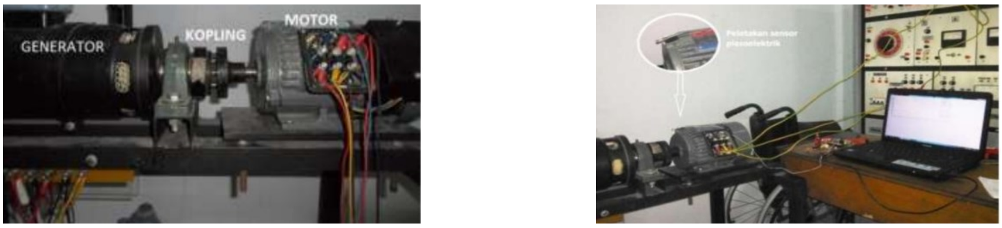


Figure 1. Misalignment classification process in induction motor

2.1. Experimental setup and study case

Laboratory experimental setup is done to simulate motor condition in normal operation, misalignment of 1mm and misalignment of 1.5 mm. Experimental scheme is shown in Figures 2 (a) and (b). Induction motor that has 0.5H P power, with a speed of 1400 RPM, 220 Volt voltage and 50 Hz working frequency paired with a generator as a mechanical load. In the installation, the generator is installed in a normal alignment condition or in the direction of the motor, 1 mm shifted and 1.5 mm shifted. And then sensor of piezoelectric is applied to measure vibration value, then it is saved to storage device by using microcontroller.



(a) (b)

Figure 2. (a) Generator and motor scheme, (b) Collect of motor vibration data condition

2.2. Discrete wavelet transform

Discrete wavelet transform (DWT) is presented in this research because it has simple calculation and relatively small time interval continuous wavelet transform. Other name of scaling/dilatation parameter is low pass filter (LPF) or it also can be called as father wavelet. and translation parameter is also called as high pass filter (HPF) or mother wavelet [13-15]. We will use both of them to do wavelet transform and inverse wavelet transform. LPF and HPF filter with different cut off frequency is used to transform signal. High frequency signal or detail signal (cD) is output from HPF and low frequency signal or approximation signal (cA) is output from LPF [16]. The relationship between LPF/father wavelet and HPF/mother wavelet can be described as in the following (1-3) :

$$\Phi_{j,k} = 2^{j/2}\Phi(2^{j}t - k), j, k \in Z) \quad (1)$$

$$\Psi(t) = \Phi(2t) - \Phi(2t - 1) \quad (2)$$

with Ψ (t) is the mother wavelet and Φ (2t) is the father wavelet. The function of the equation of the mother wavelet is (3):

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^{j}t - k), j, k \in Z \quad (3)$$

based on (1) and (3) the mother wavelet and equation (1). Full equation of DWT is explained as (4).

$$f(t) = C_{0,0}\phi(t) + \sum_{j=0}^{M-1}\sum_{k=0}^{2^{j}-1} d_{j,k}\Psi_{j,k}(t)) \quad (4)$$

The data processing process starts by passing vibration signals in HPF and LPF filters. The process will produce HF signal (cD) and LF signal (cA). Both of them have the amount of data as much as half of the original data/initial data. This process is named the 1st level decomposition process. Furthermore, LF signal (cA) will be passed again in HPF and LPF filters and will produce HF signal (cD) and LF signal (cA) at the next level. This level is called the 2nd level decomposition process. This process will continue to the desired decomposition level [17, 18].

2.3. Feature extraction

After getting high frequency signal or Detil signal (cD) from DWT, then we will calculate the feature extraction from the HF signal (cD). The HF signal (cD) processed is level of 1st to 3rd. Then, feature extraction such as sum, range, and energy, is generated from the Detil/HF signals. Range of signal is the difference between the maximum and minimum values. This can be described as (5).

Range = Max of signal – min of signal (5)

Then, sum of signal is absolute value of signal and then summed in a certain time span. This can be described as (6).

$$\text{Sum} = \sum_{n=1}^{n=k} | d(n) | \tag{6}$$

Whereas, the signal energy, e, is the sum of the squares of each signal component. This can be written as (7) [19-22].

$$e = \sum_{n=1}^{n=k} (d(n))^2 \tag{7}$$

Three of these three signal characters will be processed as input in QDA and LDA so that the condition of the motor can be known and the level of damage can be determined.

2.4. Quadratic discrinant analysis

QDA is a statistical approach to classify an amount of data into some clusters based on some characteristics. each of data in one of group will not be member in other group [23]. This is alike to multiple linear regression. The divergence lies in the type of data in the dependent and independent variables. The multiple regression is utilized in case scale of metric is used in dependent variable and either non-metric or metric scale is used in independent variable. While, discriminant analysis is utilized in case dependent variable is categorical and the independent variable utilize a metric scale.

Model of discriminant analysis is an formula that indicates a linear or quadratic composite of some independent variables, namely:

$$\mathrm{D} = \mathrm{b}_0 + \mathrm{b}_1\mathrm{X}_1 + \mathrm{b}_2\mathrm{X}_2 + \mathrm{b}_3\mathrm{X}_3 + \dots \dots + \mathrm{b}_\mathrm{k}\mathrm{X}_\mathrm{k} \tag{8}$$

from (8), it can be explained that D is the discriminant value, b is coefficient of discrimination and X is variable of independent. Value of D is uniue, so that according on the value of D, prediction of member value can be determined.

In QDA, merger of predictor variables produces zone shaped graph of quadratic function so that it is expected to produce result more precise and higher accuracy. Nevertheles, an increase in the number of predictors will make this analysis run into overfits (variability is too large) [24, 25]. Formula of QDA score to classify data into member of one of groups is in (9) as follows:

$$\hat{d}_i^Q(x) = -\frac{1}{2}\ln|S_i| - \frac{1}{2}(x - \bar{x}_i)^T S_i^{-1}(x - \bar{x}_i) + \ln p_i \tag{9}$$

with d is score value of discriminant, x is data, Si is the covariance matrix and pi is prior probability of the ith population.

3. RESULTS AND ANALYSIS

The motor is taked action in some period of time in three states, including normal condition, 1mm misalignment and 1.5 mm misalignment. The output of vibration signal is sended to data storage by vibration sensor. Then, by using matlab software, vibration data on data storage is processed. The output of vibration signal of motor is shown in the Figure 3. We can see that motor signals in normal conditions have tenuous and low value data values. When there is a 1mm of misalignment, the graph gets tighter and sometimes there are spikes. Furthermore, 1.5 mm of misalignment produces a tight graph and a high value.

3.1. Discrete wavelet transform

The next, vibration signal of induction motor is filtered using Daubechis, Coiflet and Symlet DWT. The output of DWT that is used in the next process is HF signal (cD) at level of 1st to 3rd. Predicted that at high level, idetification is more accurate. Transformed vibration signal is shown in Figures 4 (a-c). The sample of graphic in Figure 4 is the output of Daubechis 1 DWT at 1st to 3rd level. The mother wavelet applied is Daubechis 1-5, Coiflet 1-5 and Symlet 1-5. It means that vibation signal is filtered by Daubechis 1-5, Coiflet 1-5 and Symlet 1-5 as many as 3 levels, namely at 1st-3rd level. The amount of data generated and used is reduced by half of the initial data at each level. Because these data are divided into HF signal and LF signal. And at the next level, LF signal is used as input and produces HF signal and LF signal again. The resulting data still looks like random. So, this data will then be retrieved its characteristics for processing.

3.2. Feature extraction

HF signals at 1st to 3rd level resulted from the DWT process is extracted. Characteristics resulted are sum, range, and energy of signal. The output of the signal features is shown in Tables 1-3. Normally, a motor that experiences a misalignment will produce a higher vibration frequency. So that if it is processed using DWT and its characteristics are taken, the value of its characteristics will be different from the characteristics of a normal motor. This is shown in Table 1 Daubechis DWT at 1st level. The value of sum, range and energy increases significantly from normal motor until 1.5 mm misalignment motor. It's same for the other level and for other kind of DWT in Table 2 and Table 3.

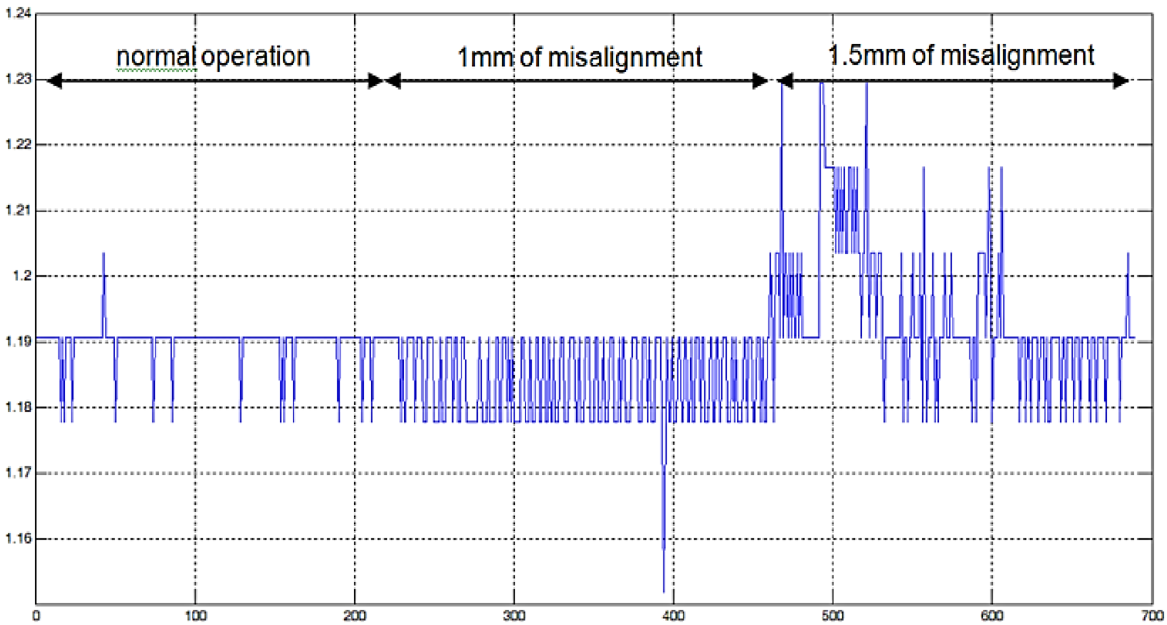


Figure 3. Vibration signal of induction motor

Table 1. Feature extraction of Daubechis 1 discrete wavelet transform

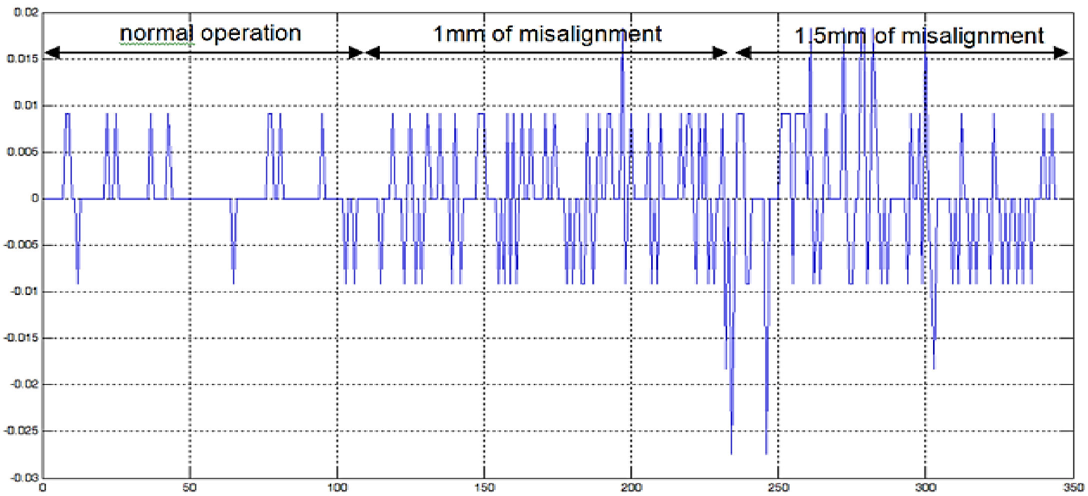
	1st Level			2nd Level			3rd Level		
	Sum	Range	Energy	Sum	Range	Energy	Sum	Range	Energy
Normal	0.1739	0.0183	0.0016	0.1100	0.0129	0.0007	0.0686	0.0092	0.0003
1mm	0.4209	0.0183	0.0039	0.2847	0.0259	0.0026	0.1739	0.0275	0.0016
1.5mm	0.5399	0.0549	0.0070	0.3429	0.0453	0.0038	0.1601	0.0229	0.0013

Table 2. Feature extraction of coiflet 1 discrete wavelet transform

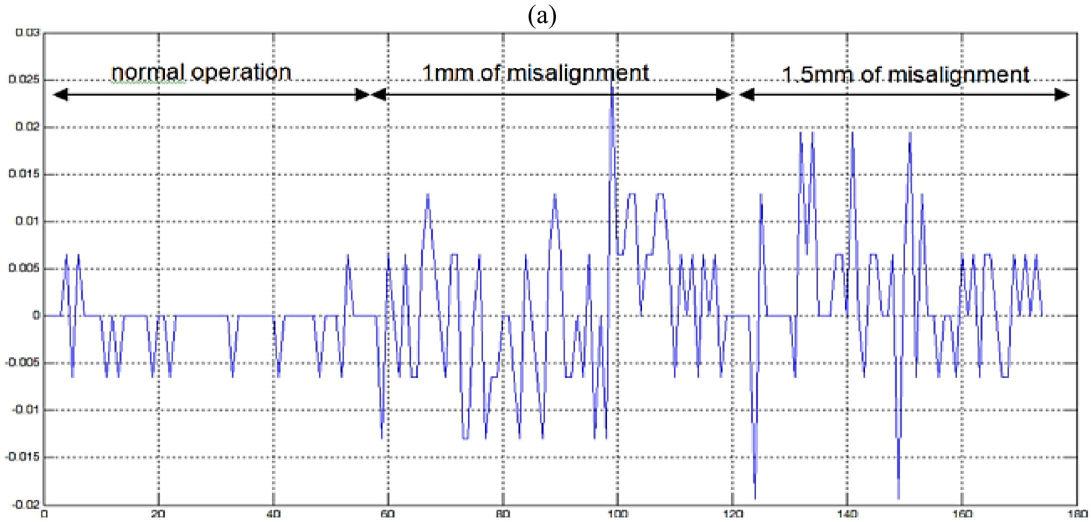
	1st Level			2nd Level			3rd Level		
	Sum	Range	Energy	Sum	Range	Energy	Sum	Range	Energy
Normal	0.2075	0.0223	0.0017	0.1057	0.0151	0.0005	0.0801	0.0171	0.0004
1mm	0.4992	0.0225	0.0034	0.3519	0.0271	0.0030	0.1975	0.0266	0.0017
1.5mm	0.6442	0.0496	0.0065	0.3493	0.0487	0.0036	0.1886	0.0241	0.0015

Table 3. Feature extraction of symlet 1 discrete wavelet transform

	1st Level			2nd Level			3rd Level		
	Sum	Range	Energy	Sum	Range	Energy	Sum	Range	Energy
Normal	0.1739	0.0183	0.0016	0.1100	0.0129	0.0007	0.0686	0.0092	0.0003
1mm	0.4209	0.0183	0.0039	0.2847	0.0259	0.0026	0.1739	0.0275	0.0016
1.5mm	0.5399	0.0549	0.0070	0.3429	0.0453	0.0038	0.1601	0.0229	0.0013



(a)



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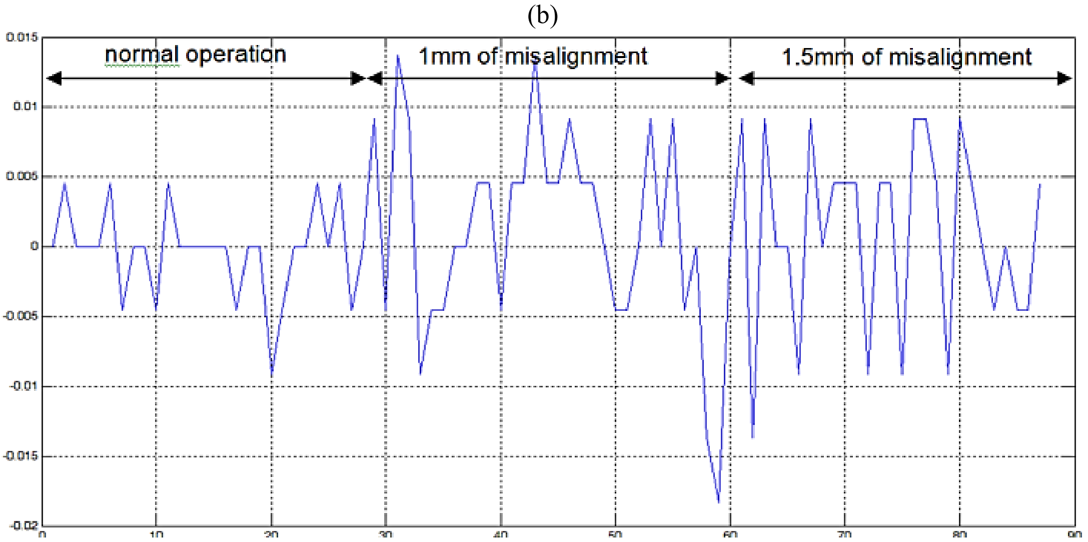

(c)

Figure 4. Daubechis 1 DWT (a) the first level (b) second level (c) third level

3.3. Discriminant analysis

QDA uses 12 training data on each normal motor, 1 mm misalignment and 1.5 mm misalignment. So all training data amounted to 36 data. Furthermore, for each normal motor condition, 1mm misalignment and 1.5 mm misalignment will be taken 8 data used as test data. So all test data amounted to 24 data.

As a comparison in measuring the accuracy of QDA, LDA is also used in processing the vibration data of this motor. QDA and LDA processing is done using matlab software. QDA and LDA output are shown in Tables 4-6.

Table 4. Classification outputs of Daubechis (Db) DWT

	1st Level		2nd Level		3rd Level	
	LDA(%)	QDA(%)	LDA(%)	QDA(%)	LDA(%)	QDA(%)
Db 1 Error	0.000	4.167	12.500	8.333	8.333	8.333
Db 2 Error	8.333	8.333	20.833	20.833	33.333	20.833
Db 3 Error	0.000	0.000	8.333	8.333	29.167	8.333
Db 4 Error	4.167	0.000	4.167	0.000	8.333	8.333
Db 5 Error	12.500	0.000	12.500	8.333	12.500	12.500

Table 5. Classification outputs of Coiflet DWT

	1st Level		2nd Level		3rd Level	
	LDA(%)	QDA(%)	LDA(%)	QDA(%)	LDA(%)	QDA(%)
Coiflet 1 Error	4.167	4.167	8.333	4.167	25.000	16.667
Coiflet 2 Error	4.167	4.167	8.333	4.167	20.833	33.333
Coiflet 3 Error	4.167	4.167	8.333	0.000	25.000	29.167
Coiflet 4 Error	4.167	4.167	4.167	8.333	25.000	33.333
Coiflet 5 Error	0.000	4.167	4.167	0.000	25.000	25.000

Table 6. Classification outputs of Symlet DWT

	1st Level		2nd Level		3rd Level	
	LDA(%)	QDA(%)	LDA(%)	QDA(%)	LDA(%)	QDA(%)
Symlet 1 Error	8.333	8.333	0.000	0.000	12.500	12.500
Symlet 2 Error	4.167	4.167	8.333	16.667	16.667	12.500
Symlet 3 Error	4.167	4.167	8.333	4.167	12.500	8.333
Symlet 4 Error	4.167	4.167	4.167	4.167	29.167	37.500
Symlet 5 Error	4.167	8.333	0.000	8.333	29.167	29.167

The table of the results of the research that has been done, consists of 15 conditions on each mother wavelet. 15 conditions are derived from variations from each mother wavelet, namely 5 types of mother wavelets multiplied by the number of levels, namely 3 levels (1^{st} level to 3^{rd} level). From the results of the research in the table above, we can see that the errors obtained from QDA and LDA using Daubechis, Coiflet and Symlet DWT vary greatly. Text with blue blocks shows that LDA is more accurate than QDA and text with green blocks shows QDA more accurately than LDA. Whereas colorless text indicates that the error results from LDA and QDA are the same.

We can see that QDA is more accurate in classifying motor conditions with cases of misalignment by processing data using Daubechis DWT. Based on Table 4, QDA is more accurate than LDA in 7 conditions, namely on Db 4 and 5 at 1^{st} level and 2nd level, Db1 at 2^{nd} level, and Db 2 and 3 at 3^{rd} level. And the error results are the same between LDA and QDA in 6 conditions. Whereas, 1 condition of LDA is more accurate.

From Table 6, we can see that LDA is more accurate than QDA in 4 conditions, namely on Symlet 2 at 2^{nd} level, Symlet 4 at 3^{rd} level, and symlet 5 at 1^{st} level and 2^{nd} level. And the error results are the same between LDA and QDA in 8 conditions. And QDA is more accurate in 3 conditions. Whereas, in Table 5, the processing of data uses Coiflet DWT, the results of the classification accuracy between QDA and LDA are the same. But at the 1^{st} level, classification errors resulted evenly from Coiflet 1-5 are very minimum.

Whereas, when viewed from the accuracy of the classification results, namely the result of an error that reaches 0%, processing data using Daubechis DWT is superior to other mother wavelets, which reaches 0% error in 5 conditions. The 0% error can be achieved using the Db1 at 1^{st} level with LDA, Db3 at 1^{st} level with LDA and QDA, Db 4 and Db 5 at 1^{st} level with QDA and Db 4 at 2nd level with QDA. When using Coiflet DWT, 0% error condition can be achieved on Coiflet 1 at 1^{st} level with LDA, and Coiflet 3 and coiflet 5 at 2^{nd} level with QDA. Meanwhile, the symlet DWT produces 0% error classification on symlet 1 at 2^{nd} level with LDA and QDA, and syimlet 5 at 2^{nd} level with LDA.

In addition, from Tables 4-6, we can see that the classification results with the minimum error value can be reached at the 1st level. While on the 3^{rd} level it produces a large enough error. It's the same whether the results are achieved by Daubechis, Symlet or Coiflet DWT. And finally, from the results of this research, we find that Daubechis DWT at 1st level is the most accurate data processing in the case of misalignment on induction motor compared to other mother wavelets. As well, QDA combined with Daubechis DWT produces the lowest classification error. However, the ability to Coiflet 1-5 DWT at the 1st level, using the method of either LDA or QDA also produces a low classification error.

4. CONCLUSION

The failure of an induction motor is a problem that gives a huge loss in the industry. One type of failure is misalignment on the induction motor. This study classifies misalignment in induction motors using three types of wavelet transforms, namely Daubechis, Coiflet and Symlet DWT and multilevel decomposition of mother wavelets, which is the 1st level to the 3rd level. The result shows that the 1st level of DWT produces the highest classification error. Then, the best classification or the most minimum classification error is produced by Daubechis DWT, especially those combined with Quadratic Discriminant Analysis (QDA). It results 0-8.33% error, depend on kind of Daubechis DWT used. Moreover, Coiflet 1-5 DWT at the 1st level produces a minimum classification error evenly. It results 4.17% of error.

However, further research needs to be done, with different induction motor power and more varied cases of misalignment, as well as more data in order to reach more accurate conclusions. That is because the results of the calcifications achieved in this study are still very varied.

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